



Research Paper

Dynamic Prototype Memory Network for Robust Multiclass Skin Lesion Diagnosis from Dermoscopic Images

Sharmila Varadan^{1*}, Shalini Shanker², Chembian Woothukadu Thirumaran³, Tupili Sangeetha⁴

1. Department of Computer Science and Engineering, School of Computing, Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Avadi, Chennai 600062, India.

2. Department of CSE, St. Joseph's Institute of Technology, Chennai, Tamil Nadu, India.

3. Department of CSE, Vel Tech High Tech Dr.Rangarajan Dr.Sakunthala Engineering College, Tamil Nadu, India.

4. Department of CSE, R.M.D. Engineering College, Kavaraipettai, Tamil Nadu, India.

Citation Varadan S, Shanker S, Thirumaran CW, Sangeetha T. Dynamic Prototype Memory Network for Robust Multiclass Skin Lesion Diagnosis from Dermoscopic Images. *International Journal of Medical Toxicology and Forensic Medicine*. 2026; 16:E53420.



<https://doi.org/10.22037/ijmtfm.v16.53420>

ABSTRACT

Article info:

Received: 10 September, 2026

Accepted: 24 September, 2026

Published: 06 October, 2026

Keywords:

Dynamic prototype memory, Skin lesion classification, Dermoscopic images, HAM10000, Prototype learning

Background: Automated skin lesion diagnosis from dermoscopic images is challenging because lesions of the same disease can vary substantially visually, while visually similar patterns can occur across different disease categories. This article introduces a Dynamic Prototype Memory Network (DPM-Net) for multiclass skin lesion classification.

Methods: We first employ a deep visual encoder to extract discriminative feature representations from dermoscopic images. We then compare the extracted lesion embeddings with disease-specific prototypes using a similarity-based prototype assignment mechanism. To enhance the method's representational capability, we dynamically update the prototypes based on the feature distribution of the lesion samples. We incorporate a prototype diversity mechanism to prevent prototype collapse, while a prototype compactness constraint encourages lesion embeddings to remain close to the representative prototypes of their corresponding disease categories.

Results: Performance validation shows improved results, with a maximum accuracy of 95.39%.

Conclusion: Therefore, the proposed model integrates different components to perform automated multiclass skin lesion diagnosis from dermoscopic images.

* Corresponding Author:

Sharmila Varada, PhD

Department of Computer Science and Engineering, School of Computing, Vel Tech Rangarajan, Dr. Sagunthala R&D Institute of Science and Technology, Avadi, Chennai, India.

E-mail: sharmisuresh2010@gmail.com



Copyright © 2026 The Author(s);

This is an open-access article distributed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (CC BY-NC 4.0);

<https://creativecommons.org/licenses/by-nc/4.0/>), which permits unrestricted non-commercial use, distribution, and reproduction in any medium, provided the original work is properly cited.

Introduction

Skin cancer is primarily caused by the uncontrolled growth of abnormal cells in the skin [1]. Dermoscopy can be used to diagnose skin cancer; it is a safe, non-surgical approach that provides high-resolution images [2]. Despite these advantages, dermoscopy faces challenges in identifying other symptoms and distinguishing different anomalies based on their size, shape, position, and color [3]. Recently, machine learning (ML) and deep learning (DL) have provided promising solutions and opened new possibilities for improving the detection of melanoma and other skin cancers [4, 5].

Several studies have examined DL-based skin lesion classification. Gabani et al. [6] developed a DCNN framework that integrates VGG16, InceptionV3, and DenseNet201 to classify skin cancers. The authors [7] designed a CNN-based model to reliably and discriminatively categorize various skin cancers. Singh et al. [8] developed an innovative DL-based system for classifying and detecting skin disorders, using a U-Net for segmentation and a transformer-based classifier with ResNet50 for skin cancer classification. Fiaz et al. [9] developed a novel DL-driven system specifically for skin cancer detection and prediction using dermoscopic images. In [10], an innovative framework for pre-processing and dataset augmentation was introduced. Two types of DL-based methods were developed using a depth-concatenation method. The authors. [11] developed a DL-driven method that performs skin cancer classification using dermoscopic images. Al-Waisy et al. [12] designed an innovative DL-based system, primarily developed for the automatic classification of skin disorders using dermoscopic images.

Although DL has improved skin lesion classification, some challenges remain. Most methods use a single representation per class, which may not capture intra-class variation or distinguish visually similar lesions. Class imbalance in datasets such as HAM10000 can also bias the learned features toward common classes, while many models use fixed class representations and separate explanation methods. In addition, their performance on independent datasets needs further evaluation. To address these issues, this study proposes DPM-Net.

Therefore, DPM-Net stores and updates multiple prototypes for each disease class. The significant contributions of this article are as follows:

- Introduce a dynamic prototype assignment and

updating mechanism to adapt disease-specific prototypes according to the incoming lesion representations.

- Incorporate prototype diversity and compactness learning to encourage distinct intra-class representations while preserving disease-specific compactness.
- Employ class-balanced prototype learning to reduce the influence of majority classes and improve the representation of minority lesion categories.
- Provide prototype-based interpretability through lesion-to-prototype similarity, allowing the learned prototype relationships contributing to predictions to be examined.

Materials and Methods

In this work, the proposed DPM-Net aims to address intra-class visual variability, inter-class similarity, and class imbalance in the multiclass skin lesion classification problem. The framework includes image preprocessing, visual feature extraction, lesion embedding, dynamic prototype memory, prototype similarity and assignment, dynamic prototype updating, prototype diversity and compactness learning, class-balanced prototype learning, prototype aggregation, and disease classification. Figure 1 illustrates the overall structure of the proposed DPM-Net.

Dataset Information

This section describes the datasets used for training, validation, and independent external evaluation of the proposed DPM-Net.

HAM10000 Dataset

The HAM10000 dataset is used as the main training and validation dataset for the proposed DPM-Net [13]. HAM10000 has 10,015 dermoscopic images from seven skin lesion classes: AKIEC, BCC, BKL, DF, MEL, NV, and VASC. NV has the most images, so class-balanced learning is used to handle the class imbalance.

ISIC 2019 Dataset

The ISIC 2019 Skin Lesion Images for Classification dataset is used solely to perform external validation of the proposed DPM-Net through an independent evaluation [14]. ISIC 2019 contains 25,331 dermoscopic images from eight classes, with seven classes matching HAM10000: MEL, NV, BCC, AK, BKL, DF, and VASC. Figure 2 presents the sample images from both datasets.

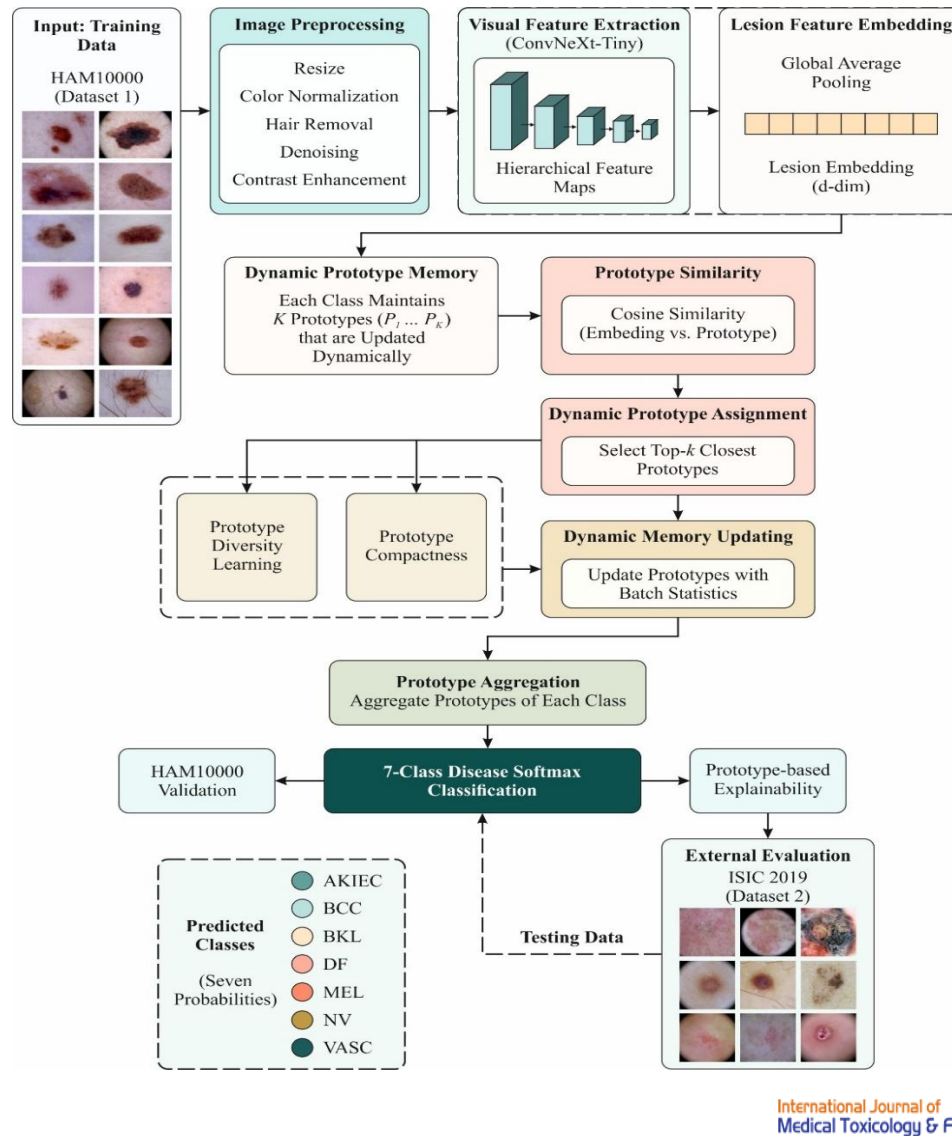


Figure 1. Processing flow of the proposed DPM-Net.

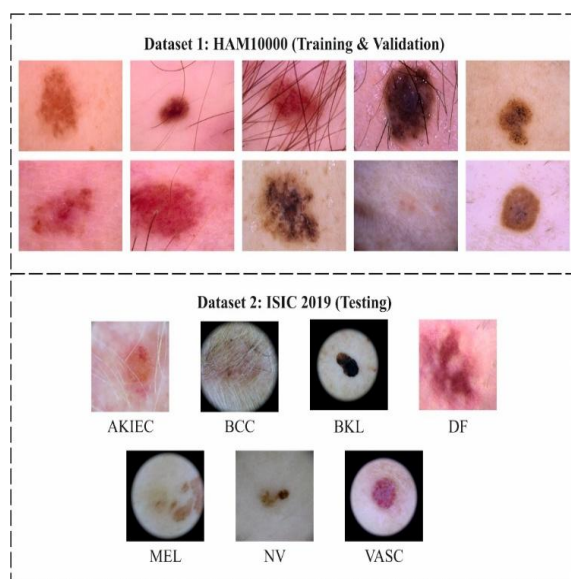


Figure 2. Sample dermoscopic images from the HAM10000 and ISIC 2019 datasets.

Visual Feature Extraction

The pretrained ConvNeXt-Tiny network is used as the visual feature encoder to extract discriminative representations from preprocessed dermoscopic images [15].

$$z = f_{\theta}(x) \quad (1)$$

$$z_p = W_p z + b_p \quad (2)$$

In the above equation, W_p and b_p denotes the weights and bias of the projection layer, and z_p is the lesion embedding. z_p is then fed into the Dynamic Prototype Memory to compute prototype similarities and assign the image to the corresponding prototypes.

Dynamic Prototype Memory

The DPM is the core module in the proposed DPM-Net. Unlike conventional classifiers trained to learn only one representation for each disease. Specifically,

this study denotes the group of prototypes for the c^{th} disease category as $\{P_c = p_{c1}, p_{c2}, \dots, p_{cK}\}$, where p_{ck} denotes the prototype of class c , and K implies the number of prototypes for each class. Given seven disease categories and $K = 4$, DPM-Net stores $7 \times 4 = 28$ prototypes dedicated to learning diverse visual representations of the different diseases.

Prototype Similarity

Once a lesion embedding z_p is obtained, the model calculates the similarity between this embedding z_p and each of the class-specific prototypes p_{ck} using cosine similarity [16].

$$S_{ck} = \frac{z_p^T p_{ck}}{\|z_p\| \|p_{ck}\|} \quad (3)$$

where z_p and p_{ck} are the lesion embedding and the k^{th} prototype of the c^{th} class, respectively. A high value of S_{ck} suggests strong correspondence between the current lesion and the k^{th} prototype of class c .

Dynamic Prototype Assignment

The model transforms similarity scores into soft assignment weights, indicating how much each prototype contributes to the lesion's representation.

$$a_{ck} = \frac{\exp(S_{ck}/\tau)}{\sum_j \exp(S_{cj}/\tau)} \quad (4)$$

Prototypes that are more similar to the lesion will be assigned larger weights, allowing the prototype memory to adapt to different lesion appearances.

Dynamic Prototype Updating

The prototypes are also dynamically updated throughout the training procedure using information from their associated lesion embeddings.

$$p_{ck}^{t+1} = (1 - \alpha)p_{ck}^t + \alpha \hat{p}_{ck} \quad (5)$$

$$\hat{p}_{ck} = \frac{\sum_{i=1}^N a_{ick} z_{p,i}}{\sum_{i=1}^N a_{ick} + \epsilon} \quad (6)$$

With this procedure, the prototype memory can progressively adapt to the underlying data distribution during training.

Prototype Diversity Learning

During training, it is possible that multiple

prototypes within the same class converge to very similar embeddings, reducing their distinctiveness. This study presents a diversity loss that penalizes high resemblance between prototypes:

$$L_{div} = \frac{1}{K(K-1)} \sum_{i \neq j} \max(0, \cos(p_i, p_j) - m) \quad (7)$$

This loss term ensures that diverse modes within a class can be captured by different prototypes.

Prototype Compactness

The aim is to ensure that each lesion remains as close as possible to the prototypes of its ground-truth class.

$$L_{compact} = \frac{1}{N} \sum_i \min_k d(z_i, p_{y_{ik}}) \quad (8)$$

This loss objective drives the lesion embeddings toward the most appropriate prototypes for their respective classes.

Class-Balanced Prototype Updating

Considering the significant class imbalance in HAM10000, the prototypes may be biased towards majority classes. To provide better supervision signals for minority classes, this study performs class-balanced sampling: training instances are sampled according to their class frequencies.

$$w_c = \frac{N}{CN_c} \quad (9)$$

Thus, this approach ensures that the prototype memory can capture diverse class representations with varying numbers of instances.

Prototype Aggregation

In order to derive the class representation from the multiple prototype contributions, the model aggregates the disease prototypes using their assignment weights. The class representation for the c^{th} disease is obtained by summing up all prototypes:

$$R_c = \sum_{k=1}^K a_{ick} p_{ck} \quad (10)$$

Here, a_{ick} and p_{ck} are the assignment weights for the i^{th} lesion and the k^{th} prototype of the c^{th} disease, respectively.

Disease Classification

The class-level representations R_c from prototype aggregation are used for final classification. The probability of the seven diagnostic categories is computed as:

$$\hat{y} = \text{Softmax}(W_R R + b_R) \quad (11)$$

Here, W_R and b_R represent the trainable weights and bias of the classification head, respectively. The model takes the class with the maximum probability as the forecasted class.

Joint Training Objective

The proposed DPM-Net model is jointly trained end-to-end by minimizing the following total loss function:

$$L_{total} = L_{CE} + \lambda_1 L_{proto} + \lambda_2 L_{div} + \lambda_3 L_{compact} \quad (12)$$

$$L_{proto} = -\frac{1}{N} \sum_{i=1}^N \log \left(\sum_{k=1}^K a_{i,y_i,k} \right) \quad (13)$$

In this definition, $a_{i,y_i,k}$ is the assignment weight of the i^{th} lesion to the k^{th} prototype of its true category y_i . $\lambda_1, \lambda_2, \lambda_3$ are balancing coefficients that control the contributions of the different losses.

Prototype-Based Explainability

The prototype assignments provide a simple way to explain each prediction. The model identifies the prototypes with the highest assignment weights for the predicted class and shows how the lesion is related to them. This links the explanation directly to the model's classification. Figure 3 shows the model's workflow, from feature extraction to explainability.

Results

Prototype learning uses 5 prototypes per class (35 total) with top-3 soft assignment based on cosine similarity, with diversity and compactness weights of 0.1 each. The model is trained with AdamW, a learning rate and weight decay of 0.0001, a batch size of 32, and 50 epochs, using cross-entropy loss with cosine annealing. Figure 4 depicts the confusion matrices of the DPM-Net approach during the training/validation phases on the HAM10000 dataset. In both matrices, the higher values on the diagonal indicate correctly classified skin lesion classes.

Figure 5 presents the testing performance of the DPM-Net approach, including a confusion matrix and a ROC curve, on the ISIC 2019 dataset. The confusion matrix indicates that higher diagonal values reflect accurate classification, with effective prediction across each skin lesion category. In addition, the ROC curves are near the upper-left corner, with AUC scores ranging from 0.992 to 1.000.

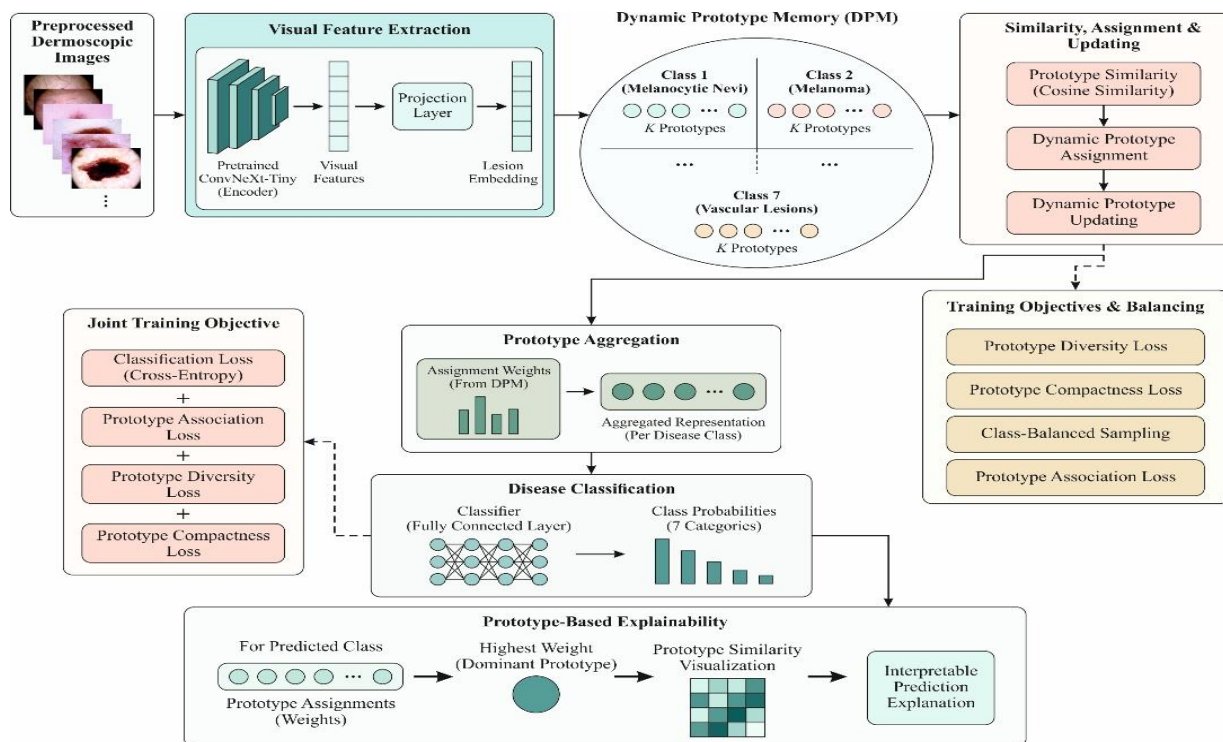


Figure 3. End-to-end architecture of the proposed DPM-Net.

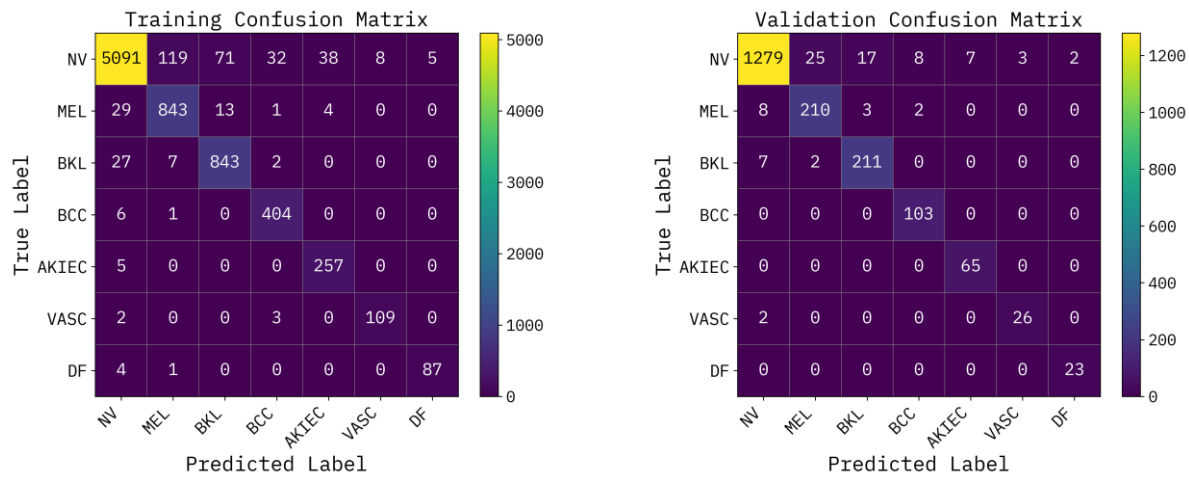


Figure 4. Confusion matrices of the DPM-Net method with training and validation sets on the HAM10000 dataset.

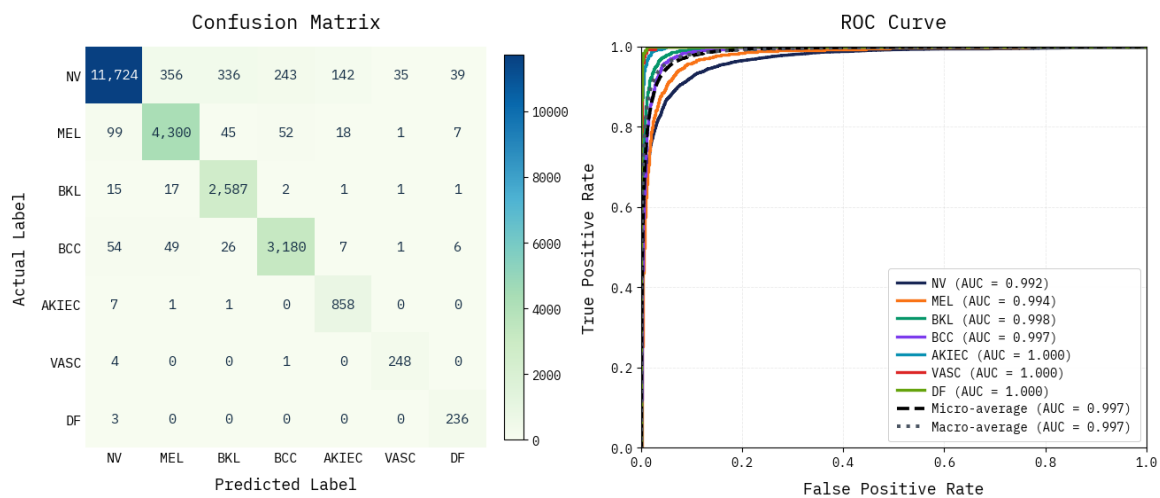


Figure 5. Testing performance of the DPM-Net method using the ISIC 2019 dataset.

Discussion

Table 1 compares the DPM-Net approach with other methodologies using the evaluation metrics [29,30]. The results indicate that Customized CNN and SCNet54 achieved lower performance, whereas GoogleNet and MobileNetV2 slightly improved performance. At the same time, the proposed DPM-Net method achieves superior performance, with an accuracy of 95.39%, precision of 91.53%, recall of 97.52%, and an F1-score of 94.35%, validating its greater capability for effective and reliable multi-class skin lesion detection.

Figure 6 shows the distances between the prototypes and skin lesion classes. Darker areas show stronger links to the corresponding classes, while

Table 1. Practical clinical framework.

Model	Accuracy	Precision	Recall	F1-score
XceptionNet	94.72	90.84	96.81	93.76
DenseNet201	92.18	89.96	94.27	91.87
GoogleNet	89.76	87.42	91.83	89.53
MobileNetV2	87.91	85.76	89.64	87.51
Customized CNN	83.68	81.94	85.72	83.47
MTANet53	91.52	90.21	92.90	91.48
SCNet54	86.32	74.06	76.76	75.38
DPM-Net	95.39	91.53	97.52	94.35

lighter areas indicate weaker links. Thus, the results show that the prototypes capture useful class-specific lesion features.

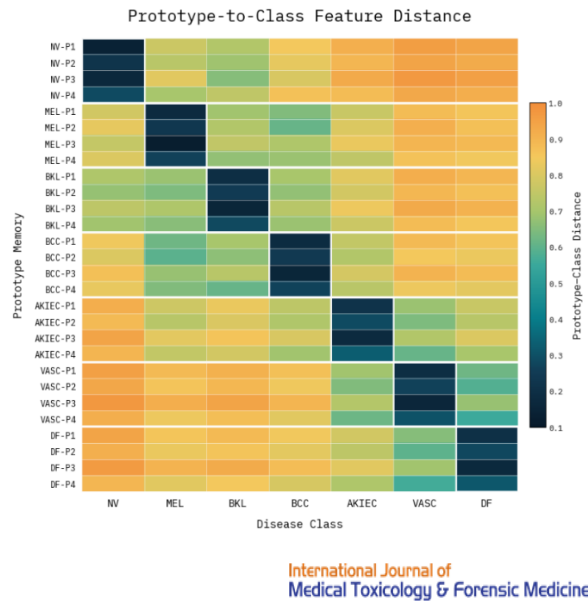


Figure 6. Prototype-to- class feature distances.

The component-wise results of the proposed model are shown in Table 2. The results indicate that the proposed model, integrating multiple components, achieved improved performance across different measures.

Table 2. Ablation study of proposed model.

Model	Accuracy	Precision	Recall	F1-Score
ConvNeXt-Tiny	91.84	87.26	91.35	89.18
ConvNeXt-Tiny + Dynamic Prototype Memory	93.12	88.94	93.16	91
ConvNeXt-Tiny + Dynamic Prototype Memory + Prototype Diversity	93.87	89.73	94.52	92.07
ConvNeXt-Tiny + Dynamic Prototype Memory + Prototype Diversity + Prototype Compactness	94.61	90.58	96.01	93.21
DPM-Net (+ Class-Balanced Prototype Learning)	95.39	91.53	97.52	94.35

In Table 3, the computation complexity results of the proposed model are examined. The results indicated that the proposed model achieved reduced computational complexity compared to other models.

Table 3. Computational complexity of proposed model.

Model	Parameters (M)	FLOPs (G)	Model Size (MB)	Inference Time (ms)	Peak Memory (MB)
XceptionNet	20.81	8.43	79.60	18.42	742.00
DenseNet201	20.01	4.39	76.30	15.76	684.00
GoogleNet	6.00	1.50	23.40	8.91	438.00
MobileNetV2	3.50	0.33	13.40	5.24	286.00
Customized CNN	4.82	0.71	18.40	6.38	321.00
MTANet53	12.64	2.18	48.20	10.83	497.00
SCNet54	13.71	2.47	52.30	11.46	523.00
DPM-Net	2.86	0.27	10.90	4.31	241.00

Conclusion

This paper presents DPM-Net, a method for multi-class skin lesion classification that uses multiple dynamic prototypes for each disease class. The approach captures different lesion patterns within the same class and updates the prototypes as new samples are processed. Class-balanced prototype learning helps reduce the effect of the unequal class distribution in HAM10000, while prototype diversity and compactness help maintain clear class representations. The model is trained on HAM10000 and externally evaluated on the seven common classes of ISIC 2019 without fine-tuning, showing its ability to generalize across datasets. In future work, prototype selection can be made more dynamic, and the method can be tested on larger multi-center datasets, with prototype-based explanations further adapted for clinical use.

Ethical Approval

Not applicable.

Acknowledgment

None.

Funding

No external funding was received for this research.

Conflicts of Interest

The authors report there are no competing interests to declare.

References

- [1] Singh ID, Bansal S, Datta P. Automated Multi-Class Skin Disease Diagnosis Using Deep Convolutional Neural Networks. In: 2026 Fourth International Conference on Secure Cyber Computing and Communications (ICSCCC). IEEE; 2026. p. 1308-13. [DOI: [10.1109/ICSCCC69031.2026.11600163](https://doi.org/10.1109/ICSCCC69031.2026.11600163)]
- [2] Ravisankar S, Karthikeyan M. Deep learning-based multi-class classification of cutaneous lesions for dermatological assessment. *Cutan Ocul Toxicol.* 2026;1-19. [DOI: [10.1080/15569527.2026.2702002](https://doi.org/10.1080/15569527.2026.2702002)]
- [3] Christy SJ, Kumari GRN. An Optimized Deep Learning Framework for Robust Multi-Class Skin Cancer Detection from Dermoscopic Images. In: 2026 13th International Conference on Computing for Sustainable Global Development (INDIACom). IEEE; 2026. p. 1-5. [DOI: [10.23919/INDIACom70271.2026.11525716](https://doi.org/10.23919/INDIACom70271.2026.11525716)]
- [4] Nikhitha K, Mayee MK, Bhavya G, Chandana MM, Subhashini T, Sailaja M. Multi-Class Skin Diseases Detection Using Dermoscopic Images. In: 2026 Fourth International Conference on Augmented Intelligence and Sustainable Systems (ICAISS). IEEE; 2026. p. 882-7. [DOI: [10.1109/ICAISS68683.2026.11526239](https://doi.org/10.1109/ICAISS68683.2026.11526239)]
- [5] Saju JK, Thakur D, Sharma P, Pandey A, Tajammul M. A Deep Learning Framework for Automated Multi-Class Skin Disease Detection Using Dermoscopic Images. In: 2026 5th International Conference on Innovative Practices in Technology and Management (ICIPTM). IEEE; 2026. p. 1-8. [DOI: [10.1109/ICIPTM69057.2026.11465623](https://doi.org/10.1109/ICIPTM69057.2026.11465623)]
- [6] Gabani V, Navamani TM, Shyamala K, Vaswani Rajpal VK. Multimodal skin lesion classification for early cancer diagnosis using deep learning. *Front Physiol.* 2026;17:1717517. [DOI: [10.3389/fphys.2026.1717517](https://doi.org/10.3389/fphys.2026.1717517)]
- [7] Chand HV, Sabharwal S, Jiang W, Islam SM, Cengiz K. A stacking-based deep learning ensemble for multi-class skin lesion classification. *Discov Comput.* 2026;29(1):417. [DOI: [10.1007/s10791-026-10288-6](https://doi.org/10.1007/s10791-026-10288-6)]
- [8] Singh MK, Singh AK, Choudhary P, Singh AK, Tyagi LK. A practical deep learning framework for multi-class skin cancer detection using U-Net segmentation and ResNet50 transfer learning. *J Niger Soc Phys Sci.* 2026;3530. [DOI: [10.46481/jnsps.2026.3530](https://doi.org/10.46481/jnsps.2026.3530)]
- [9] Fiaz M, Shoaib Khan MB, Khan AH, Bilal A, Abdullah M, Darem AA, et al. An explainable hybrid deep learning framework for precise skin lesion segmentation and multi-class classification. *Front Med.* 2025;12:1681542. [DOI: [10.3389/fmed.2025.1681542](https://doi.org/10.3389/fmed.2025.1681542)]
- [10] Arshad M, Khan MA, Almujaally NA, Alasiry A, Marzougui M, Nam Y. Multiclass skin lesion classification and localization from dermoscopic images using a novel network-level fused deep architecture and explainable artificial intelligence. *BMC Med Inform Decis Mak.* 2025;25(1):215. [DOI: [10.1186/s12911-025-03051-2](https://doi.org/10.1186/s12911-025-03051-2)]
- [11] Owida HA, El-Fattah IA, Abuowaida S, Alshdaifat N, Mashagba HA, Abd Aziz AB, et al. A deep learning-based dual-branch framework for automated skin lesion segmentation and classification via dermoscopic Images. *Sci Rep.* 2025;15(1):37823. [DOI: [10.1038/s41598-025-21783-z](https://doi.org/10.1038/s41598-025-21783-z)]
- [12] Al-Waisy AS, Al-Fahdawi S, Khalaf MI, Mohammed MA, Al-Attar B, Al-Andoli MN. A deep learning framework for automated early diagnosis and classification of skin cancer lesions in dermoscopy images. *Sci Rep.* 2025;15(1):31234. [DOI: [10.1038/s41598-025-15655-9](https://doi.org/10.1038/s41598-025-15655-9)]
- [13] Skin Cancer MNIST: HAM10000 Dataset. Kaggle. Accessed August 1, 2026. [Link]
- [14] ISIC 2019 Skin Lesion images for classification dataset. Kaggle. Accessed August 1, 2026. [Link]
- [15] Liu Z, Mao H, Wu CY, Feichtenhofer C, Darrell T, Xie S. A convnet for the 2020s. In: 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). IEEE; 2022. p. 11966-76. [DOI: [10.1109/CVPR52688.2022.01167](https://doi.org/10.1109/CVPR52688.2022.01167)]
- [16] Snell J, Swersky K, Zemel R. Prototypical networks for few-shot learning. *Adv Neural Inf Process Syst.* 2017;30.
- [17] Li X, Ouyang J, Chen Y, Diao Z, Li K, He D, et al. Accurate skin lesion classification on imbalanced dermoscopic images with high

- variance via the SCTFD framework. Sci Rep. 2026;16(1):12302. [DOI: [10.1038/s41598-026-37846-8](https://doi.org/10.1038/s41598-026-37846-8)]
- [18] Sarhan AM, Ali HA, Yasser S, Gobara M, Kandil AA, Sherif G, et al. Achieving high-accuracy skin cancer classification with deep learning optimized by ant colony algorithm. J Electr Syst Inf Technol. 2025;12(1):49. [DOI: [10.1186/s43067-025-00243-8](https://doi.org/10.1186/s43067-025-00243-8)]